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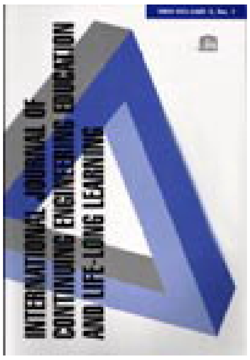

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Indicators and characteristics of career visualisation ability based on cloud computing

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Abstract: Professional core competitiveness is the content that all countries in the world pay attention. Especially in the information age, with the rapid development of artificial intelligence, how to better adapt to the professional environment is an urgent problem that needs to be solved. At present, there are problems with the evaluation of occupational visualisation ability and feature construction, such as large data differences, difficulty in fusion, and difficulty in efficiently extracting and standardising various occupational data. Moreover, due to the lack of adaptability and flexibility in the adopted technical means, the ability to analyse and express data is limited. To solve this problem, this paper takes cloud computing as the main technology and constructs an index system of individual visualisation ability. It meets the requirements of modern personnel training and promotes social development base on meeting individual development needs. The index system includes five dimensions: learning development ability, work communication ability, organisational integration ability, career transformation ability, and emotional control ability. There are four reference variables under each dimension. The reliability analysis of the scale of this index system shows that the internal consistency reliability coefficient, retest reliability coefficient, and split-half reliability coefficient of other subscales and total scales are above 0.84, except for the three reliability coefficients of career transformation ability subscales ranging from 0.75 to 0.77.

Keywords: cloud computing technology; professional ability improvement; visual indicators of vocational ability; professional ability characteristics.

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1 Introduction

Cloud can be defined as a new computing paradigm, providing users with scalable, on-demand, and virtualised resources. In this type of computing, users can access a shared pool of computing resources, which are provided with minimal management efforts of users. Cloud computing, as an internet-based way of transmitting and utilising computing resources, can provide users with on-demand access to computing resources such as servers, storage, and databases. It is based on the background of enterprises' requirements for high efficiency, flexibility, and scalability of IT resources. However, there are some obstacles and concerns in the use of the cloud. Ensuring the service quality of service providers can be regarded as one of the main concerns of companies that tend to use IT. With the characteristics of multi-tenancy, flexibility, rapidity, and easy expansion, it can significantly reduce the operating cost and improve the operating efficiency, which has been widely concerned by the business and academic circles.

Career visualisation refers to the visualisation of career information related to job requirements, vocational skill requirements, salary levels, etc., through data visualisation methods. Employees' career development is related to the specific socio-economic and cultural background. Western scholars often define and construct individuals' career adaptability from the career development concepts of 'self-realisation', 'self-construction' and life design. At present, enterprises are becoming increasingly critical and demanding on the quality of labour force, and higher requirements are put forward for the professional specialty and work flexibility of individual labour force. As the professional ability is gradually concerned and recognised by all walks of life, improving the professional ability of workers has become the starting point and destination of various research fields.

This paper fully utilises the massive data processing capabilities of cloud computing platforms to collect and integrate multi-source employment big data. On this basis, using analytical methods, the main factors that affect the development of vocational abilities are identified, and an evaluation model that can reflect the changing trends of the job market is constructed. By utilising the flexibility and scalability of cloud computing technology, personalised visualisation tools are provided to users, enabling real-time analysis and display of data. The research in this paper can provide some help for the employment of enterprises and the promotion of individual professional ability, evaluate employees' professional ability from more dimensions, and allow employees have a full understanding of their professional ability accomplishment. The innovations of this paper are as follows: cloud computing and data mining technology are applied to the research of occupational visualisation capability indicators and characteristics, and a cloud deployment scheme is designed; a multi-dimensional and reliable index system of occupational visualisation ability is constructed, and an individual-oriented measurement table is formed. The use of cloud computing technology provides users with an efficient and scalable data management mechanism, effectively reducing the system's requirements for memory and computation. On this basis, advanced big data analysis methods are utilised to establish personalised occupational ability characteristic models and achieve personalised indicator evaluation. By utilising the collaborative nature of cloud computing, data sharing and collaboration among multiple enterprises can be achieved, thereby promoting knowledge exchange and technology integration between enterprises.

2 Related work

In the current rapidly changing labour market environment, career development and management have become important issues of concern for both enterprises and individuals. Against the backdrop of increasingly diversified career development paths and the need for individual self-development, how to efficiently evaluate and enhance employees' career visualisation has become an important research issue (Goteng et al., 2022). The current research mainly focuses on how to construct a scientific and reasonable evaluation index system to accurately measure the clarity of individual career planning (Jiang et al., 2023; Liu et al., 2023). A study aimed at understanding the vocational abilities of senior high school students and assisting in their future planning utilised a questionnaire that assessed individuals across seven different dimensions of professional ability. The scale was tested through stratified random sampling on 55 senior high school students. The results indicated no significant difference in professional ability between male and female students (Priyanga and Nancy, 2019). Osinska et al. (2018) introduced and discussed the analysis of personal activities or a single scientific career path, and developed a web application program to visualise the scientific achievements of specific researchers. This free software provided six analysis layouts based on bibliographic data of local database. Researchers can see the dynamic characteristics of their writing activities, the time and place of publication, and the subject range of research questions. They can also determine the cooperation network, so as to study the correlation and regularity in their own scientific activities. Tran (2020) focused on reviewing the career structure, and then empirically analysed the relationship between female employees' career adaptability and job satisfaction. The results showed that three of the four components of occupational adaptability were called occupational attention, occupational control, and occupational confidence, which had a positive impact on women's satisfaction in the current occupation. The industry difference between occupational adaptability and job satisfaction drew a conclusion, which supported the use of occupational construction theory to further study the relationship between occupational adaptability and other career life outcomes of female employees. These studies provide some guidance for vocational competency assessment, but they are inefficient and lack flexibility.

Cloud platforms have powerful computing, storage, and analysis capabilities, providing more possibilities for enhancing the transparency, flexibility, and operability of personal career planning (Islam et al., 2023; Karamchand, 2024; Rosenzweig et al., 2024). In the era of Web 2.0 based on big data, information graphics are shared through social media, which is a method for many enterprises including individuals to share information efficiently. However, the empirical research on the characteristics of SNS users and the types and characteristics of information graphics is not enough. Therefore, the purpose of this study is to understand the characteristics of different types through the street type information map shared in SNS, and to provide information map making guidelines to effectively transmit information (Lee, 2017). Mobile cloud integrates mobile and cloud computing to expand their functions and advantages and overcome their limitations. Tawalbeh et al. (2017) discussed the role of mobile cloud and big data analysis in its implementation. They described the mobile cloud infrastructure based on cloudlet for big data applications. The technologies, tools, and applications of big data analysis were reviewed. The service provision in the cloud is based on the service level agreement, which represents the negotiated contract between users and providers. If the supplier fails to meet the agreed application requirements, it shall pay a fine as compensation. The researchers comprehensively investigated the model of the realisation principle proposed in the literature to address the quality of service (QoS) guarantee problem (Ghahramani et al., 2017). Ozyurt et al. (2022) investigated the latest career opportunities and demand areas and skill sets in cloud computing, revealing 22 skill areas and 46 skills that reflect the interdisciplinary background of cloud computing work, and created a skill map that illustrates the correlation between cloud computing and its related skills. Khedkar (2024) explored all the key elements for building a thriving career in the cloud computing field, emphasising the importance of cloud specific capabilities across various platforms, including network design, security principles, and programming automation, highlighting how they impact market value and career development. George et al. (2023) summarised that cloud adoption was driving the transformation of IT work and proposed to use key skills such as cloud architecture, security, and development to improve future employability and ensure that IT workers have a stable career in the technological environment. Goteng et al. (2022) described a collaboration with the Amazon Web Services (AWS) Academy to redesign the undergraduate module on cloud computing. Academic theories were integrated into cloud computing and its applications through industry connections, enabling students to possess theoretical and practical knowledge and skills. Research found that when theoretical knowledge and understanding were combined with real-world applications through industry connections, students' vocational skills learning outcomes were better. Existing research has provided certain standards for vocational ability assessment, but there are generally problems in the application of technical tools and data presentation, such as slow response to dynamically changing job market demands, insufficient cross disciplinary data integration, and lack of personalised analysis.

3 Research methods of career visualisation capability indicators and characteristics based on cloud computing

3.1 Index evaluation method

3.1.1 Factor analysis method

Factor analysis is a statistical method used to study the intrinsic structure or dimensions between observed variables and identify the fundamental factors that affect these variables. The common factor of factor analysis is a common influencing factor that cannot be directly observed but exists objectively. Each variable can be expressed as the sum of the linear function of the common factor and the special factor:

$$\begin{cases} Y_1 = m_{11}G_1 + m_{12}G_2 + \ldots + m_{1n}G_n + \varepsilon_1 \\ Y_2 = m_{21}G_1 + m_{22}G_2 + \ldots + m_{2n}G_n + \varepsilon_2 \\ \vdots \\ Y_q = m_{q1}G_1 + m_{q2}G_2 + \ldots + m_{qn}G_n + \varepsilon_q \end{cases} \tag{1}$$

G is a common factor, and ε_i is a special factor. Common factors and special factors are irrelevant, with variance of 1, and each special factor is irrelevant. m_{ij} indicates the degree of dependence of Y_i on G_i. The greater the absolute value, the higher the degree of closeness. The model expressed by matrix is:

$$\mathbf{Y} = \mathbf{MG} + \boldsymbol{\varepsilon} \tag{2}$$

The matrix **M** composed of m is called factor load matrix. The factor load matrix can be solved by principal component analysis. It is necessary to calculate the covariance matrix $\mathcal{H}$ of the original data first, and then calculate its eigenvalues λ and corresponding eigenvectors t, $\mathcal{R}$, which is a matrix composed of unit eigenvectors, so that the covariance matrix can be obtained:

$$\mathcal{H} = \mathcal{R}\begin{bmatrix} \lambda_1 & \ldots & 0 \\ 0 & \ddots & 0 \\ 0 & \ldots & \lambda_q \end{bmatrix}\mathcal{R}^{\mathrm{T}} = \left(\sqrt{\lambda_1}t_1, \ldots, \sqrt{\lambda_q}t_q\right)\begin{bmatrix} \sqrt{\lambda_1}t_1^T \\ \vdots \\ \sqrt{\lambda_q}t_q^T \end{bmatrix} \tag{3}$$

Ignoring the special factors, it can be concluded that:

$$\mathcal{H} = D(Y) = D(AG) = AD(G)M^T = MM^T \tag{4}$$

$$M = \left(\sqrt{\lambda_1}t_1, \sqrt{\lambda_2}t_2, \ldots, \sqrt{\lambda_q}t_q\right) \tag{5}$$

Factor analysis is to reduce the dimension, so the number of factors n is less than the number of original variables q. In the final calculation process, only the first n feature roots and corresponding feature vectors need to be advanced:

$$M = \left(\sqrt{\lambda_1}t_1, \sqrt{\lambda_2}t_2, \ldots, \sqrt{\lambda_n}t_n\right) \tag{6}$$

The sum of squares of elements in line I of the load matrix M is the commonness of variables, which is:

$$y_i^2 = \sum\nolimits_{j=1}^{n} m_{ij}^2 \tag{7}$$

$$D(Y_i) = m_{i1}^2 D(G_1) + m_{i2}^2 D(G_2) + \ldots + m_{in}^2 D(G_n) + D(\varepsilon_i) \tag{8}$$

$$D(Y_i) = y_i^2 + \sigma_i^2 \tag{9}$$

The sum of squares of the elements in column j of the load matrix is the contribution of the factor G_i to Y, which measures the importance of the factor.

$$r_j^2 = \sum\nolimits_{j=i}^{q} m_{ij}^2 \tag{10}$$

$$r_j^2 = \left(\sqrt{\lambda_j}\, t_j\right)^T \left(\sqrt{\lambda_j}\, t_j\right) = \lambda_j \tag{11}$$

One of the purposes of factor analysis is to explain common factors. However, one variable may have a greater load on multiple common factors, or multiple variables may have a greater load on the same factor. In this case, the load coefficient matrix can be rotated so that each variable has the maximum load on only one variable, and the elements in the same column are close to 1 or 0 (Choi and Ko, 2017; Jie, 2017).

3.1.2 Analytic hierarchy process

An important concept in analytic hierarchy process is hierarchical structure, which systematically divides a problem into multiple influencing factors, establishes an analytic hierarchy process structure according to the relationship among factors, and divides the multiple constituent factors of a problem into multiple levels dominated by upper and lower levels. The analytic hierarchy process can transform complex decision-making problems into structured processes and use pairwise comparisons to determine the importance of each factor, in order to make more scientific and reasonable decisions. This method can effectively solve the problem of mixing subjective and objective information, and is suitable for multi-objective decision-making situations.

Judgement matrix is a matrix established by pairwise comparison and assignment of the importance of each factor of a certain level relative to that of the previous level according to a certain judgement scale (Wang et al., 2019).

Then, the consistency of the judgement matrix is judged, and the consistency ratio CR is used as an index to measure the consistency of the judgement matrix. When the value of CR is less than 0.1, the original matrix has satisfactory consistency; otherwise, the judgement matrix is modified.

$$CR = \frac{CI}{RI} \tag{12}$$

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{13}$$

CI is the consistency index; *RI* is the randomness consistency index, and the RI of the 1–9 order judgement matrix is shown in Table 1.

Table 1 Average random consistency index

Order	*RI*
1	0
2	0
3	0.52
4	0.89
5	1.12
6	1.26
7	1.36
8	1.41
9	1.46

The next step is to determine the importance of factors through hierarchical sorting, which requires the eigenvector *W* and the maximum eigenvalue of the judgement matrix *A* to complete. The judgement matrix *A* is normalised by column to obtain matrix *B*:

$$B = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{14}$$

The elements of matrix *B* are added in rows to obtain a new vector *b*, and the eigenvector *W* is obtained after normalisation:

$$W = \frac{a_i}{\sum_{i=1}^{n} a_i} \tag{15}$$

W is the importance degree of each factor; *A* is a fuzzy subset, and its largest characteristic root can be obtained:

$$\lambda_{\max} = \frac{1}{n} \sum_{i=1}^{n} \frac{(AW)_i}{W_i} \tag{16}$$

3.1.3 Fuzzy comprehensive evaluation

When making a fuzzy comprehensive evaluation of things, the first step is to establish the evaluation scale of each factor, use the set *A* to represent the evaluation grade and q to represent the actual evaluation factors, and synthesise the evaluation sets of all factors to obtain the fuzzy relation matrix *P* from *Q* to *A*.

$$A = \{a_1, a_1, \ldots, a_n\} \tag{17}$$

$$Q = \{q_1, q_1, \ldots, q_n\} \tag{18}$$

$$P = (p_{ij}) = \begin{Bmatrix} P_1 \\ P_2 \\ \vdots \\ P_m \end{Bmatrix} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mn} \end{bmatrix} \tag{19}$$

The fuzzy relation matrix from Q to P reflects the degree to which each factor belongs to each level in the hierarchy. When evaluating the whole evaluation object, it is necessary to use the weight of each factor to synthesise the membership degree of fuzzy subsets at each level. This process is a fuzzy comprehensive process, and the comprehensive evaluation result vector can be obtained:

$$R = A \circ P = \{a_1, a_2, \ldots, a_n\} \circ \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mn} \end{bmatrix} \tag{20}$$

3.2 Vocational ability characteristic model

According to the individual's ability and quality, the iceberg model divides the ability features into explicit features that can be perceived at the top of the iceberg and implicit features that are hidden under the iceberg (Fan et al., 2021; Ishikura et al., 2018). As shown in Figure 1. The upper layer of iceberg, including knowledge and skills, is easily perceived and evaluated by the outside. Implicit characteristics refer to traits and motives, which are difficult to be evaluated; there is also self-concept, which is between explicit features and implicit features. In the ability evaluation of most types of professional workers, the knowledge and skills of the upper layer of the iceberg are mostly related to the job qualification and can be measured in a short time. However, it is difficult to accurately describe the characteristics of the lower iceberg and formulate measurement standards, which can only be reflected when the subjective initiative of its work changes and affects its work.

The onion model embodies the basic elements of ability and quality and shows the observable and measurable characteristics of each element. From the inside out, ability and quality can be summarised as a multi-level structure, and motivation is the core of the structure. Then, from the inside out, it develops into personality, self-image, values and social role attitudes, knowledge and skills (Xiaohui, 2021). The ability of the outer layer is easier to cultivate and evaluate, and the ability of the inner layer is more difficult to evaluate and acquire. The onion model is shown in Figure 2.

The onion model, as a hierarchical model used to depict corporate culture and individual capabilities, can be likened to an onion wrapped in layers from the inside out, with each level corresponding to a characteristic or capability factor. It helps to understand individual abilities and the complexity of corporate culture, helping educators, managers, and individuals recognise their own development needs and develop targeted growth plans. Through a progressive approach, the onion model emphasises a gradual exploration from shallow to deep to promote overall and deep development.

Figure 1 Competency iceberg model (see online version for colours)

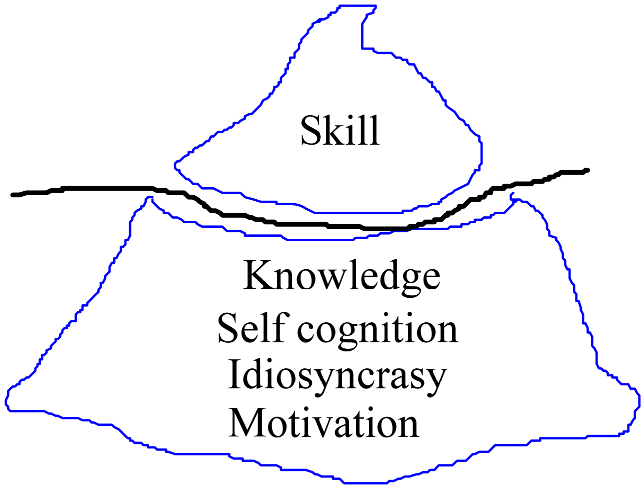
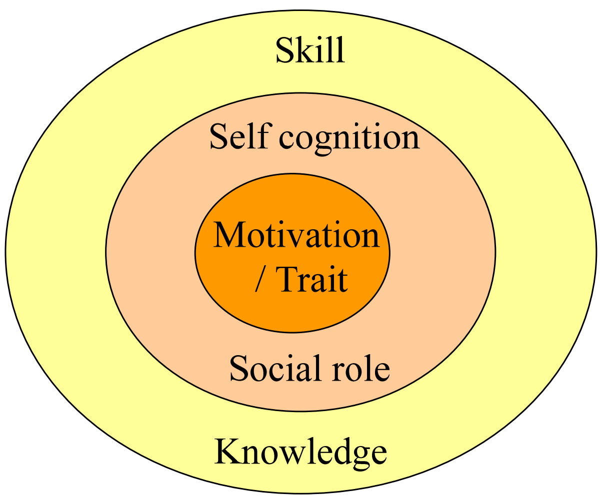


Figure 2 Onion model (see online version for colours)



4 Research experiment on the indicators and characteristics of career visualisation based on cloud computing

4.1 Vocational ability evaluation system based on cloud computing

Through cloud computing server, database server, and internet connection application, the bottom layer of the system integrates computer clusters and resources through IaaS services to provide basic services for users. Cloud platform mainly integrates the underlying data of vocational ability evaluation through VMware virtual management system; the upper layer mainly adopts VMware virtual desktop management system;

users also use VMware virtual desktop management system and access the cloud computing platform for unified management (Tang et al., 2018).

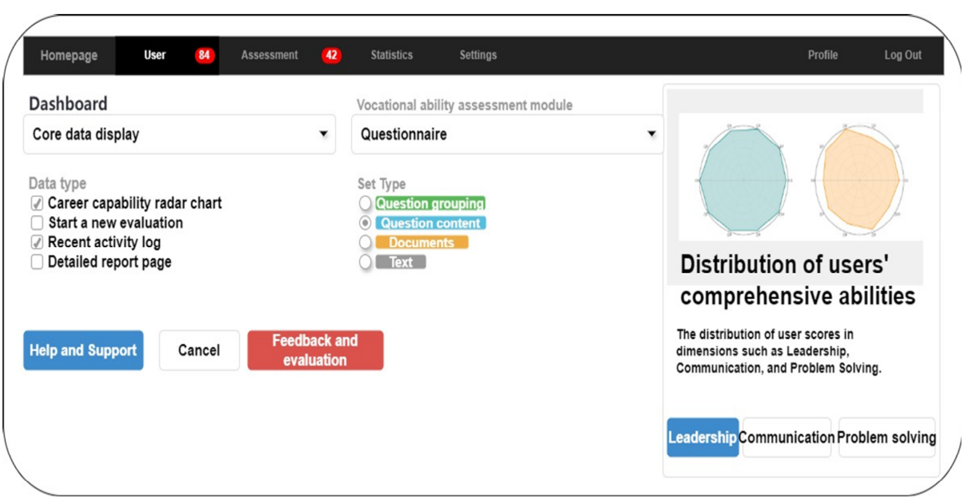
This paper is based on a cloud-based career competency assessment system, which mainly includes a user interface, data collection module, data analysis engine, cloud computing platform, and reporting and visualisation tools. For the development of personal professional competence model, it is necessary to collect data of self-evaluation and mutual evaluation of enterprises and employees by means of cloud management platform of cloud computing, and form a big dataset. Then, the big data processing and mining capabilities of cloud computing are used to develop the visual model of professional competence. The model needs to include quantitative and qualitative indicators. The fuzzy comprehensive evaluation method should be used to determine the indicators, and the hierarchy of indicators and the weight of each level of indicators should be determined by AHP. This is the next key research of this paper.

4.2 System development and functional implementation

This paper is based on cloud computing, fully leveraging the scalability and scalability of the IaaS layer, and combining it with virtualisation technology to achieve efficient data processing and integration. On this basis, the VMware virtual management system is utilised to integrate basic hardware resources, virtualising computing clusters, storage devices, network devices, etc., onto a unified cloud computing platform to ensure high availability and flexibility of the system.

In terms of tool selection for development, a microservice architecture is constructed using the SpringCloud framework in the backend, enabling modular development and dynamic expansion; using Vue in the front-end, the JS framework is used for dynamic human-computer interaction, ensuring a smooth system and a good user experience. At the same time, this project also uses Hadoop distributed file system as the data storage platform, combined with technologies such as Spark, to achieve big data analysis and mining in professional talent ability assessment.

Figure 3 System testing interface (see online version for colours)



In terms of functional implementation, the system is designed around five core modules: user interface, data collection module, data analysis engine, cloud computing platform, and reporting and visualisation tools.

1 User interface

 As the first interface between the system and users, the user interface ensures that users can have consistent operating experience on both PC and mobile phones through adaptive design of various terminal devices. In this interface, functions such as filling out vocational ability test questionnaires, viewing results, and submitting feedback are integrated together. Users only need one click to complete the entire process from data input to result output. The system testing interface of this paper is shown in Figure 3.

2 Data collection module

 The data collection module mainly summarises self-evaluation and peer evaluation data of enterprises and employees, standardises the data input in a structured form, and supports batch uploading, making it convenient for enterprise managers to input massive employee data at once. To protect user privacy, various sensitive information of users has been encrypted to maintain high security in transmission, storage, and other processes. In terms of data manipulation, the data collection module supports a large number of inputs and outputs to facilitate the processing of large amounts of data.

3 Data analysis engine

 The data analysis engine is based on machine learning algorithms and continuously optimises the accuracy of evaluation results by learning historical data. In terms of data analysis, Apache Spark's big data processing architecture is utilised to achieve analysis of big data. Based on historical data, the career level that users may reach at a certain point in the future is predicted, and personalised career planning and development paths are designed for them.

4 Cloud computing platform

 The cloud computing platform provides support for various components. Through IaaS services, computing and storage resources are virtualised to build a resilient and scalable cloud computing environment. VMware's virtual management system mainly integrates the evaluation basic data of professional talents, while VMware's virtual desktop management system uniformly manages user access. To ensure the security and privacy of data, multiple layers of security mechanisms such as access control and log auditing are adopted to ensure the security of enterprise and personal data in cloud storage and processing.

5 Report and visualisation tools

 The report and visualisation tools help users have a visual understanding and utilisation of the analysis results. This module mainly converts complex data analysis results into a visual graph, presenting the distribution of user scores in various professional abilities in a radar graphic manner to compare the ability gaps between user groups and identify key areas where professional abilities are insufficient.

4.3 Professional ability characteristics and index system construction

Taking the reality faced by employees' career development as the anchor point and solving practical problems facing reality as the starting point, the empirical dimension of visualisation of professional ability is constructed. This step is also made clear through the expert interview method, and the vocational ability evaluation is preliminarily determined as five dimensions, namely, learning development ability, work communication ability, organisational integration ability, career transformation ability, and emotional control ability, which may be expressed by A–E in the following research.

Table 2 Measurement form

A Learning development ability							
Does your professional knowledge meet the job requirements?	1	2	3	4	5	6	7
Do your existing job skills meet the job requirements?	1	2	3	4	5	6	7
Can you learn new knowledge and skills well?	1	2	3	4	5	6	7
Can you sum up your experience and improve yourself?	1	2	3	4	5	6	7
B Work communication ability							
How is your ability to communicate well with colleagues?	1	2	3	4	5	6	7
How do you handle interpersonal relationships at work?	1	2	3	4	5	6	7
How do you communicate with customers?	1	2	3	4	5	6	7
How do you handle the relationship between superiors and subordinates?	1	2	3	4	5	6	7
C Organisational integration ability							
Do you adapt to the business model of the company?	1	2	3	4	5	6	7
Do you agree with the company rules and regulations?	1	2	3	4	5	6	7
What do you think of the management style of your leader?	1	2	3	4	5	6	7
What is your attitude towards the company's environment?	1	2	3	4	5	6	7
D Career transformation ability							
When the position changes, your status	1	2	3	4	5	6	7
When the career prospects are not satisfactory, your status	1	2	3	4	5	6	7
When looking for a career again, your status	1	2	3	4	5	6	7
When faced with being dismissed, your state	1	2	3	4	5	6	7
E Emotion control ability							
When work pressure is high, your status	1	2	3	4	5	6	7
When work encounters setbacks, your state	1	2	3	4	5	6	7
When given extra work, your status	1	2	3	4	5	6	7
When the customer demands too much, your status	1	2	3	4	5	6	7

The above dimensions cover all the problems in employees' career development, and its conceptual extension is relatively complete. Among them, learning development ability refers to the ability of individuals to integrate learning resources and make up for the deficiency when there is still a gap between their own knowledge and skill structure and the current job requirements. Communication ability refers to the ability of individuals to communicate well and effectively with others at work, which is mainly reflected in accurately conveying work instructions, feedback, and other paralanguage information; organisational integration ability refers to solving the problems between individuals and corporate culture and management, which is mainly reflected in the degree of conformity of values; career transformation ability mainly solves the problem of career transformation among employees in different positions and enterprises; emotional control ability mainly solves the individual's ability to solve stress problems, that is, the individual's emotional control ability when work is difficult or interpersonal frustration occurs (Zhang et al., 2018; Liu and Zhao, 2017).

If the professional ability is set as the first level indicator, these five dimensions are the second level indicator in the individual professional ability evaluation system, and the third level indicator is also determined by the expert interview method. Dimension A includes variable professional theory, work skills, learning efficiency, and experience summary, which is represented by A1–A4. Dimension B contains variables: colleague communication, interpersonal relationship, customer communication, and parent-child relationship represented by B1–B4; dimension C includes variables, such as working environment, rules and regulations, business model, and management model, which are represented by C1–C4. Dimension D includes variables such as job change, development prospect, dismissal, and career expectation, which are represented by D1–D4, respectively. Dimension E contains variables such as work pressure, work frustration, extra workload, and high customer requirements, which are represented by E1–E4, respectively.

The measurement method is presented in the form of a question, with a score of 7 degrees, as shown in Table 2.

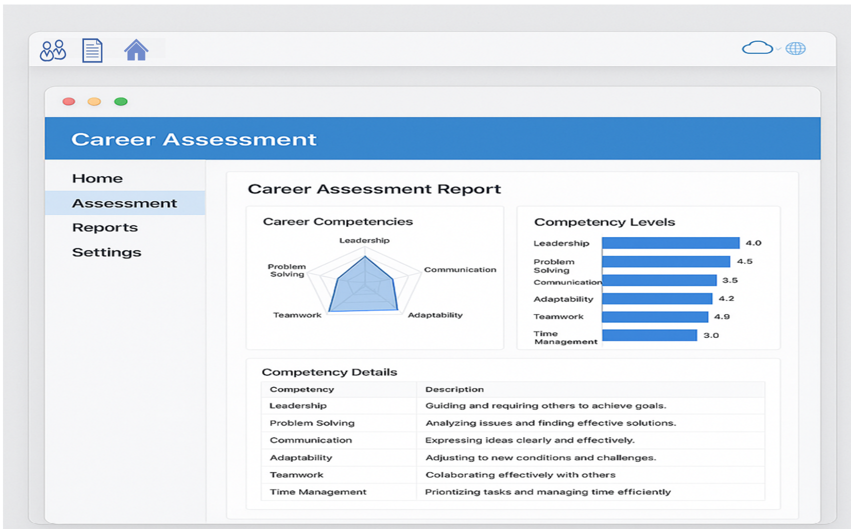
4.4 System applications

In order to verify the practicality of the cloud computing-based visual assessment system for professional abilities, a two-week questionnaire survey was conducted on enterprises in various industries. The system is deployed on VMware's virtual desktop management platform, and enterprises can access the platform through their internal network to register, evaluate, and submit data. The manager will assign a testing task to each person, and each participant will conduct a self-assessment based on their job position using a cloud computing-based visual assessment system. At the same time, direct supervisors and colleagues will conduct mutual evaluations. With the support of Hadoop computing engine, real-time data is uploaded to the cloud and automatically cleaned and modelled. The system automatically models and visualises the ability structure in the background, and finally forms a personal ability report, as shown in Figure 4.

From Figure 4, it can be seen that the report covers the radar chart of occupational ability assessment, ability level scoring, and ability detail description.

In terms of data collection, 380 and 270 questionnaires are distributed in the initial test phase, and a total of 650 questionnaires are distributed. The survey subjects cover a variety of industries including manufacturing, catering, sales, engineering and construction, communications and finance, as well as various functional positions such as production technology, administrative office, sales and service, etc. After the questionnaires are collected, they are strictly screened to eliminate invalid questionnaires with missing information and confusing answer logic, and finally, 602 valid questionnaires are collected. When entering data, two people are required to enter the data. After the entry is completed, the data is cleaned up; the integrity and rationality of the data are checked; the abnormal values are verified and processed.

Figure 4 Visual assessment of professional abilities based on cloud computing (see online version for colours)



In the formal testing phase, samples covering more than 30 industries including IT, chemicals, real estate, engineering and construction, hotels, retail, and medicine are selected, and a total of 1,500 test questionnaires are distributed. After the questionnaires are collected, they are also processed according to the screening criteria of the initial test, and 1,143 valid samples are finally obtained. During the data processing process, professional statistical software is used to analyse the data. The extreme group method is used to analyse the discrimination of scale items. The subjects are divided into high-score group and low-score group according to their scores. The score differences between the two groups on each item are calculated to test whether the items can distinguish subjects with different ability levels. If the sig value of the variance test is less than 0.5, the item discrimination is considered good. For the homogeneity test, the product-moment correlation coefficient between the item and the total score is calculated. The correlation coefficient is significant at the –0.05 level, and the higher the value, the higher the homogeneity between the item and the latent variable.

First, the scale is initially tested, mainly in M province and Q province. A total of 380 copies are distributed in M province, 270 copies in Q province and 650 copies in total. After eliminating invalid questionnaires, 602 copies are recovered. The samples involve various functions of various industries, as shown in Figure 4.

The collected samples are analysed to see if the scale can reflect the professional competence level of different testers, mainly using extreme group method and homogeneity test method (Kaur and Sharma, 2018). First, the extreme group method is used to analyse the project discrimination, and the inspection results are shown in Figure 5. It can be seen that the sig values of all variance tests are less than 0.5. At this time, it can be considered that all items of the scale can well distinguish the different professional abilities of the subjects, and the degree of discrimination of these items can meet the requirements.

Figure 4 Initial test samples of the scale (see online version for colours)

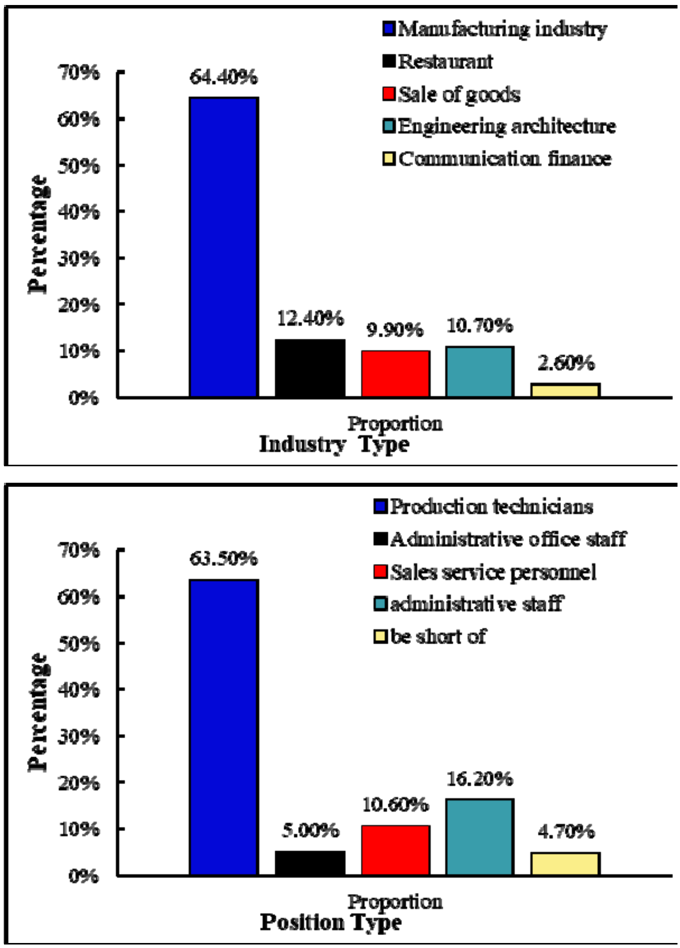


Figure 5 Extreme group test of indicators in each dimension (see online version for colours)

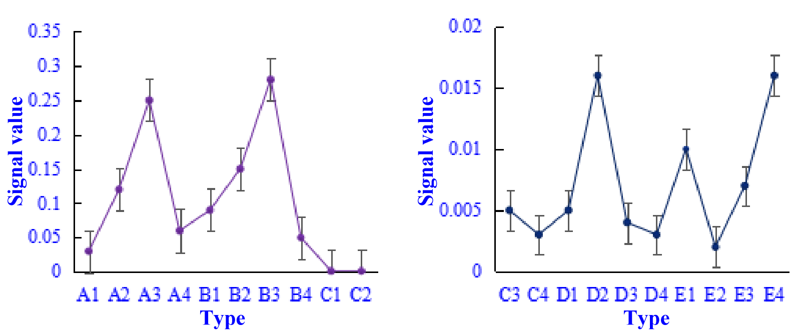


Table 3 Correlation coefficient matrix between each test component and total score of test dimension

			A Learning development ability		
	A1	*A2*	*A3*	*A4*	*Sum*
A1	1				
A2	.73**	1			
A3	.56**	.70**	1		
A4	.69**	.64**	.64**	1	
Sum	.84**	.86**	.86**	.83**	1
			B Work communication ability		
	B1	*B2*	*B3*	*B4*	*Sum*
B1	1				
B2	.71**	1			
B3	.53**	.63**	1		
B4	.64**	.62**	.67**	1	
Sum	.85**	.86**	.86**	.85**	1
			C Organisational integration ability		
	C1	*C2*	*C3*	*C4*	*Sum*
C1	1				
C2	.83**	1			
C3	.73**	.74**	1		
C4	.66**	.65**	.66**	1	
Sum	.90**	.88**	.87**	.83**	1
			D Career transformation ability		
	D1	*D2*	*D3*	*D4*	*Sum*
D1	1				
D2	.58**	1			
D3	.43**	.42**	1		
D4	.36**	.39**	.41**	1	
Sum	.76**	.77**	.73**	.74**	1
			E Emotion control ability		
	E1	*E2*	*E3*	*E4*	*Sum*
E1	1				
E2	.63**	1			
E3	.62**	.54**	1		
E4	.43**	.39**	.52**	1	
Sum	.82**	.81**	.84**	.73**	1

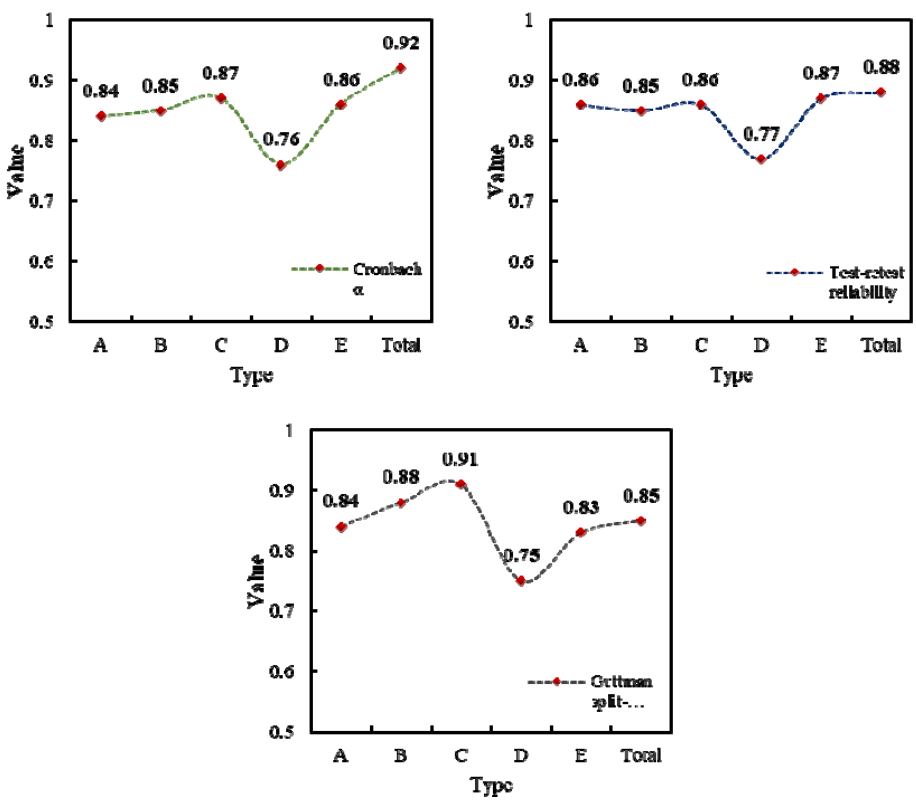
Item screening also needs homogeneity test. This step is mainly to find the correlation between items and the total score, to judge the consistency between each item and the overall scale, and to find the product-moment correlation coefficient matrix between each component and the total index, as shown in Table 3. From the table, it can be seen that the correlation coefficients between each component item of vocational ability and the total score range from .73 to .90, and all of them are significant at the level of .05, which indicates that they are highly correlated, and there is high homogeneity between all items and latent variables, so there is no need to delete variables. Therefore, the contents of this preliminary measurement table can be retained for further research.

To test the validity of the scale, firstly, KMO test is carried out on the representativeness of the sample, and then Bartlett test is carried out. The KMO value is .908, which indicates that the sampling is representative enough. The approximate chi-square of Bartlett test is 5,123.76, which is unusually significant. It shows that the theoretical construction validity of the initial scale is ideal.

Table 4 KMO and Bartlett tests

KMO metric		.90
Bartlett sphericity test	Approximate chi-square	5,123.76
	df	192
	Sig.	.000

Figure 6 Reliability test of vocational ability evaluation form (see online version for colours)



The formal test is conducted, and the selected samples cover more than 30 industries, including IT, chemical industry, real estate, engineering and construction, hotels, retail, and medicine. A total of 1,500 test questionnaires are distributed; 1,200 are returned; 1,143 valid samples are obtained. The reliability and validity of this formal sample are tested around five competency dimensions, mainly starting from retest reliability, homogeneity reliability, and split-half reliability test method. The results are shown in Figure 6. The internal consistency reliability and split-half reliability of the formal scale are tested, and the results show that the reliability of the vocational ability evaluation test scale is good.

Figure 6 shows the reliability test results of the career competency assessment scale. The Cronbach's α coefficient is used to measure the internal consistency of the scale. The closer the coefficient is to 1, the higher the correlation between the items in the scale and the stronger the reliability of the scale. The Cronbach's α coefficient of the learning and development ability dimension (A) is 0.84; the work communication ability dimension (B) is 0.85; the organisational integration ability dimension (C) is 0.87; the emotional control ability dimension (E) is 0.86; the total scale is 0.92, indicating that the internal consistency of the scale is good; the Cronbach's α coefficient of the career transformation ability dimension (D) is 0.76, which is relatively low and within an acceptable range. The retest reliability reflects the stability of the scale's measurement results at different times. The retest reliability of the learning and development ability dimension (A) is 0.86; the work communication ability dimension (B) is 0.85; the organisational integration ability dimension (C) is 0.86; the career transformation ability dimension (D) is 0.77; the emotional control ability dimension (E) is 0.87; the total scale is 0.88, indicating that the scale has good stability. The split-half reliability is to divide the scale into two halves and calculate the correlation between the scores of the two halves. The split-half reliability of the learning and development ability dimension (A) is 0.84; the work communication ability dimension (B) is 0.88; the organisational integration ability dimension (C) is 0.91; the career transformation ability dimension (D) is 0.75; the emotional control ability dimension (E) is 0.83; the total scale is 0.85, which further verifies the reliability of the scale. Comprehensively considering various reliability indicators, it is shown that the reliability of the professional ability assessment test scale is good.

5 Discussion

Based on the data of cloud computing, this paper studies the indicators and characteristics of vocational visualisation ability, constructs a cloud deployment system for obtaining individual vocational ability indicators, and constructs a vocational ability adaptability index system with complete denotation and connotation in a qualitative and quantitative way. Firstly, this paper summarises the research contents related to cloud computing technology and professional ability visualisation, and summarises the previous research experience and research focus. Secondly, it describes the hierarchical structure of cloud computing, the virtualisation deployment scheme of cloud computing, and the organisational structure of cloud resource management platform and cloud resource service portal. Thirdly, the methods of index evaluation and construction mainly include factor analysis, analytic hierarchy process, and fuzzy comprehensive evaluation method, which lays a methodological foundation for the following research. Then, the characteristics model of vocational ability is summarised, mainly introducing two models, namely the famous competency iceberg model and onion model, which provides a theoretical reference for the initial establishment of the following indicators. Next, it is the core content of this paper, that is, the construction of the index system of vocational ability. Firstly, this content determines five dimensions of vocational ability evaluation, namely, learning development ability, work communication ability, organisational integration ability, career transformation ability, and emotional control ability. Four variable indicators are set for each dimension, forming a vocational ability measurement scale. The initial test of the scale is carried out; a small range of samples are selected; the consistency of the results is tested, which proves that the initial test scale has a good degree of discrimination between samples, and the reliability and validity can meet the requirements. Finally, the final test of the scale is carried out, and a wide range of samples are selected. The reliability of the scale is measured by three methods. The results show that the vocational ability index system has good reliability.

6 Conclusions

Professional competence refers to a series of special abilities that individuals need to adapt to environmental changes and solve practical problems in their career development. It covers organisational integration, work communication, learning expansion, emotional regulation, and career transformation, and is an important psychological parameter for measuring career development. In the context of difficult economic structural transformation, limited career choices, and intensified competition, individual professional competence directly affects personal growth and corporate development. This paper constructs a visual index system for professional competence and identifies five dimensions: learning and development ability, work communication ability, organisational integration ability, career transformation ability, and emotional control ability. Each dimension contains four variable indicators to form a professional competence measurement scale. Through preliminary and formal tests, the scale is rigorously tested for reliability and validity. The results show that the scale has good reliability and validity, which provides support for the visualisation research of professional competence index. The study has certain limitations, including the high dependence on cloud computing services, which may cause data security and privacy risks, and network delays that affect real-time data processing efficiency, and the universality of the index system in different industries and cultural backgrounds needs to be verified. Future research can be improved from aspects such as strengthening data security protection, optimising network architecture to reduce delays, and expanding the scope of application of the index system to improve the security, timeliness and applicability of the system.

Declarations

All authors declare that they have no conflicts of interest.

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